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Determinants of Behavioral Intention Toward Chatbot Adoption for Customer Relationship Management (CRM) Among Organizational Users in Vietnam

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ABSTRACT

In the context of AI technologies increasingly embedded in enterprise systems, chatbot-integrated Customer Relationship Management (chatbot-CRM) has emerged as a strategic tool to enhance customer service and internal efficiency. This study extends the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB) by adding compatibility, efficacy, facilitating conditions, and resistance to change to investigate the determinants of behavioral intention to adopt chatbot-CRM systems among organizational users in Vietnam. Data were collected through a survey of 147 participants working in CRM-using organizations and analyzed using PLS-SEM. The findings reveal that attitude toward using and perceived behavioral control significantly shape behavioral intention to use chatbot-CRM. Perceived usefulness, ease of use, and compatibility positively affect user attitudes, while efficacy and facilitating conditions positively enhance perceived behavioral control. In contrast, subjective norms and resistance to change were not significant, indicating that internal perceptions of value and assistance outweigh external social pressures in this context. The study offers new insights into chatbot-CRM adoption in emerging markets and implications for the adoption of AI-integrated CRM solutions.

Keywords: chatbot, CRM, chatbot-CRM, AI-integrated CRM, organizational users, TAM, TPB.

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1. Introduction

The integration of artificial intelligence (AI) into enterprise systems has become a key driver of digital transformation in modern organizations. Among these, chatbot-enabled CRM systems represent a significant innovation, providing the potential to improve customer engagement, automate routine tasks, and improve internal operational efficiency (Ozay et al., 2024). As such technologies are increasingly invested in and deployed, understanding the behavioral factors affecting successful adoption becomes crucial, particularly from the perspective of internal users who interact with these systems on a daily basis.

While many studies have been conducted on AI-chatbot adoption from the end user's standpoint in various sectors (Pillai & Sivathanu, 2020; Ashfaq et al., 2020; Li et al., 2023; Marjerison et al., 2025; Alagarsamy & Mehrolia, 2023; Hasan et al., 2023), the insights into the usage intention of organizational users, including employees and managers who play an important role in implementing chatbot-CRM systems, have not been examined properly (Brachten et al., 2021). There are crucial differences in context and user expectations between an external customer chatbot and an internal enterprise chatbot integrated with CRM. While the former chatbot is typically designed to serve customers by boosting customer experience, resolving queries quickly, and enhancing service satisfaction (Ashfaq et al., 2020), the latter chatbot is a tool used by employees within their work environment to assist them in tasks, automate parts of workflows, or provide information from enterprise systems (Brachten et al., 2021). The introducing a chatbot-CRM might alter job roles or workflows and affect the firm performance (Chatterjee et al., 2021; Chatterjee et al., 2023; Chatterjee et al., 2022), which contrasts with external users who can simply choose not to use a chatbot during their service experience. Similarly, in Vietnam, although AI-based CRM solutions have been increasingly adopted across various industries such as retail, finance, and services, prior studies have emphasized exploring the technical system design and customer-side interactions (Ngoc & Ngan, 2025; Nguyen et al., 2023; Hai et al., 2024).

To address this gap, this study investigates the determinants of behavioral intention to adopt chatbot-CRM systems among organizational users in Vietnam. Based on the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB; Davis, 1989; Ajzen, 1991), the research model is extended with contextual factors such as compatibility, efficacy, facilitating conditions, and resistance to change, to consider both technological perceptions and organizational readiness elements (Brachten et al., 2021; Rogers et al., 2014; Urbani et al., 2024; Chatterjee, Rana, et al., 2023; Chatterjee et al., 2022).

The study is guided by the following research questions:

RQ1. What factors influence an organization's behavioral intention to use chatbot-CRM systems in Vietnam?

RQ2. To what extent do internal perceptions outweigh social influence in shaping chatbot-CRM behavioral intention to use in organizational settings?

By prioritizing the underexplored factors of internal adoption in an emerging digital economy, this study contributes to both academic research and managerial strategies for implementing the chatbot-CRM system effectively in Vietnamese organizations and in similar markets.

2. Literature review

2.1. Chatbot-CRM system

Customer Relationship Management (CRM) systems have developed beyond the original function of storing customer information and tracking sales (Glazer, 1997) into sophisticated platforms integrating various internal processes and external networks "to create and deliver value to targeted customers" (Ozay et al., 2024; Buttle & Maklan, 2019). With the integration of AI, businesses can optimize CRM to understand, forecast, and deliver products or services satisfying the evolving needs of customers (Ozay et al., 2024). For instance, leading CRM platforms in the world such as Salesforce, HubSpot, Zoho CRM, Pipedrive, Freshworks, Monday.com, and Creatio have integrated chatbot functions, enabling 24/7 personalized customer services via conversational interfaces that often feel human-like (Murtarelli et al., 2021). Moreover, the chatbot-CRM systems also support employees by taking over routine or repetitive tasks from them, enabling them to focus on more complex tasks (Khneyzer et al., 2024). Therefore, organizations may benefit from cost savings, faster responses, and improved data-driven insights. However, launching chatbots into established workflows often requires substantial change management, employee training, and process re-engineering, requiring employees to adjust their routines and trust the chatbot's performance in serving customers.

In Vietnam, local platforms such as FPT.AI, AntBuddy, and Stringee offer chatbot-CRM solutions which are often deployed on widely used messaging platforms such as Zalo and Facebook Messenger (Nguyen et al., 2023). However, there is limited research focusing on the adoption of this system by organizational users. Most studies focus on the technical development of Vietnamese-language chatbots or individual customer perspectives in specific sectors. A recent study in Vietnam's banking sector found factors like trust and satisfaction influenced ongoing use (Nguyen et al., 2021), while Hai, et al. (2024) investigated that technological anxiety, perceived chatbot reliability, and employee IT skills as determinants of adoption. However, no comprehensive study has yet integrated classical technology acceptance theories with factors tailored to the Vietnamese organizational context. This study thus situates the current study in the nexus of global chatbot-CRM research and the specific context of Vietnam, underscoring the need to investigate the determinants of chatbot adoption intentions in Vietnamese organizations to both enrich the literature and guide practitioners in successful chatbot-CRM implementation in Vietnam.

2.2. Theoretical background

2.2.1. Technology Acceptance Model (TAM)

One of the widely usable models for explaining and predicting user's technology adoption is the Technology Acceptance Model by Davis (1989). TAM indicates that perceived usefulness (PU) and perceived ease of use (PEU) determine an individual's attitude toward using a new system, which in turn influences behavioral intention and actual usage. First, PU is defined as " the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989). This means that if users perceive a chatbot-CRM to offer faster customer query resolution and better data management, they are more likely to accept it. Second, PEU refers to "the degree to which a person believes that using the system would be free of effort" (Davis, 1989). This captures the user's expected comfort and simplicity in learning or interacting with the chatbot interface. Additionally, TAM suggests that PEOU can indirectly boost adoption by increasing the perceived usefulness of the system (Davis, 1989). This study applies the TAM model in the context of how different perceptions about organizational users influence intention to use the chatbot-CRM. Furthermore, the TAM model is extended in this study by incorporating compatibility, as proposed in Rogers' Diffusion of Innovation theory to assess the extent to which the chatbot-CRM is perceived as fit to users' current work practices and organizational culture (Rogers et al., 2014). This extension is also empirically supported by a systematic review conducted by Rahimi, et al. (2018) , which found that compatibility is the most commonly added construct to TAM model. However, even when employees recognize the potential usefulness of new systems, they may still resist adoption due to disruptions to established workflows or fear of change (Kim & Kankanhalli, 2009). Thus, this study include resistance to change to the model to better capture internal users' relectance toward chatbot-CRM implementation.

2.2.2. Theory of planned behavior (TPB)

As the TAM model excludes many contextual or personal factors such as users' attitude and subjective norms, this research also develops a model based on the Theory of Planned Behavior (TPB) by Ajzen (1991). TPB postulated that an individual's behavioral intention to perform a behavior is determined by attitude toward the behavior, subjective norms, and perceived behavioral control (Ajzen, 1991). Attitude toward the behavior (AT) is defined as "the degree to which a person has a favorable or unfavorable evaluation or appraisal of the behavior in question" (Ajzen, 1991). If employees believe that adopting a chatbot-CRM will have beneficial outcomes, they will hold a more favorable attitude toward using it. Subjective norms (SN) refer to "the perceived social pressure to perform or not to perform the behavior" (Ajzen, 1991). This might involve management encouraging the use of chatbots, or colleagues' opinions about AI tools, which can sway an individual's intention to comply. Perceived behavioral control (PBC) is defined as "the perceived ease or difficulty of performing the behavior", accounting for both internal capabilities and external resources (Ajzen, 1991). In this context, PBC may include users' belief in their capability to utilize the chatbot system, which can be referred to as efficacy, and the availability of resources such as training or IT support, which can be referred to as facilitating conditions.

By combining TAM and TPB, this study captures both the individual technology perceptions and the organizational context factors that determine adoption intention.

3. Research hypotheses and model

3.1. Perceived usefulness

Perceived usefulness (PU) is defined as the degree to which individuals believe that the chatbot-CRM will improve their job performance or effectiveness (Davis, 1989). In an organizational context, a chatbot-CRM deemed useful may help employees respond to customer queries faster, manage customer data more efficiently, or enhance service quality. When employees perceive a chatbot-CRM as advantageous to their work outcomes, they are more inclined to accept it (Chatterjee et al., 2020). Chatterjee, et al. (2020) found that PU had a strong positive effect on employees' intention to use AI-enabled CRM systems in Indian enterprises. Similarly, Brachten, et al. (2021) noted that employees must be convinced of the tool's usefulness for themselves to be willing to adopt enterprise chatbots. Thus, we propose the following hypothesis:

H1a. Perceived usefulness positively affects attitude towards using chatbot-CRM.

3.2. Perceived ease of use

In this study, perceived ease of use (PEU) is defined as the degree to which the chatbot-CRM is perceived as free of difficulty or effort. Even a very useful technology can face resistance if it is complex or intimidating to use. Within organizations, employees are often busy and may not have patience for tools that have a steep learning curve or usability issues. Based on the TAM model, previous studies emphasized the importance of PEOU, implying that when a chatbot-CRM interface offers a user-friendly interfacr and blends effortlessly with established workflows, employees are more likely to adopt it (Brachten et al., 2021; Urbani et al., 2024; Chatterjee et al., 2020; Chatterjee et al., 2021). A chatbot-CRM system that is easy to interact with reduces anxiety and effort, thereby enhancing the user's attitude and willingness to use it. Thus, the following hypotheses are formulated:

H1b. Perceived ease of use positively affects perceived usefulness.

H1c. Perceived ease of use positively affects attitude towards using chatbot-CRM.

3.3. Compatibility

Compatibility (COM), proposed in the diffusion of innovation theory (Rogers et al., 2014), refers to the extent to which the chatbot-CRM is consistent with an organization's existing work practices, values, and infrastructure (Brachten et al., 2021; Chatterjee et al., 2023). If the adoption process of chatbot-CRM involves minimal changes to the current CRM software, data workflows, and the way employees already work, the chatbot-CRM is likely accepted. Urbani, et al. (2024) emphasized that COM and interoperability with legacy systems is a key consideration for adoption. Previous studies also showed that perceived COM is a determinant of attitude towards new technologies, as users feel the innovation meshes with their job requirements and organizational context (Brachten et al., 2021; Urbani et al., 2024; Chatterjee et al., 2023). Thus, we propose the following hypothesis:

H1d. Compatibility positively affects attitude towards using chatbot-CRM.

3.4. Attitude towards using chatbot-CRM

Attitude (AT) is the overall favorable or unfavorable assessment of using chatbots for CRM systems (Davis, 1989; Ajzen, 1991). In this study, AT plays a central mediating role, which is determined by PU, PEU, and COM, and in turn, influences the intention to adopt chatbot-CRM. A positive AT means the employees like the idea of using the chatbot-CRM, and find it appealing or beneficial, whereas a negative AT means they find the idea of using it not worthwhile. Previous studies showed that AT mediates the effects of PEU and PU on intention, and has a dominant effect on employees' usage intentions, more than other TPB factors (Brachten et al., 2021; Ngoc & Ngan, 2025; Chatterjee et al., 2020; Chatterjee et al., 2021). When internal users genuinely believe that using chatbot-CRM is a good idea and feel positive about it, they are very likely to intend to use it. Thus, the following hypothesis is proposed:

H2. Attitude towards using chatbot-CRM positively affects behavioral intention to use chatbot-CRM.

3.5. Subjective norms

Subjective norms (SN) capture the perceived social pressure to use the chatbot-CRM, resulting from the beliefs about whether important people at the workplace want an employee to use it (Ajzen, 1991). Regarding organizational context, these important people include top management, direct supervisors, and colleagues or team members. If an employee perceives that leadership strongly supports the chatbot-CRM and expects everyone to use it, or if their peers are enthusiastically adopting it, the employee may feel a normative pressure to comply. Recent studies showed that having support from these important people as external influences could bolster employees' confidence in using chatbot-CRM (Brachten et al., 2021; Chatterjee et al., 2021). Thus, we propose the following hypothesis:

H3. Subjective norms positively affect behavioral intention to use chatbot-CRM.

3.6. Efficacy

Efficacy (E) in this context refers to an employee's belief in their own ability to effectively use the chatbot-CRM (Taylor & Todd, 1995). Employees with high computer self-efficacy are confident that they can learn and master the new chatbot-CRM, while those with low self-efficacy may doubt their capability to adapt. In enterprise technology adoption, employees who feel assured in troubleshooting basic technological issues or learning new interfaces will accept chatbot-CRM with less fear and more openness. Brachten, et al. (2021) added efficacy in the TPB model and showed it contributes to higher PBC over using enterprise chatbots. Thus, we propose the following hypothesis:

H4a. Efficacy positively affects perceived behavioral control.

3.7. Facilitating conditions

Facilitating conditions (FC) refers to the degree to which an employee believes that sufficient organizational and technical resources exist to support the usage of chatbot-CRM (Brachten et al., 2021; Chatterjee et al., 2023). This includes training, helpdesk support, compatible hardware or software, and management policies, which remove external barriers and enable employees to transform their intentions into actual usage. The literature found that FC positively influences technology usage in organizations, either directly or via enhancing PBC or AT (Brachten et al., 2021; Chatterjee et al., 2023). However, this study considers FC as an internal availability resource of the organizations. Thus, we propose the following hypothesis:

H4b. Facilitating conditions positively affect perceived behavioral control.

3.8. Perceived behavioral control

Perceived behavioral control (PBC) in this study refers to the employee's perception of their ability to use the chatbot-CRM, encompassing both personal control and external constraints (Ajzen, 1991). This means that if individuals feel they have the requisite skills and a supportive environment, they are more likely to intend to use chatbot-CRM regularly. Brachten, et al. (2021) found that employees' efficacy and facilitating conditions accounted for 72% of the variance in PBC in terms of chatbot use. This emphasizes that when employees feel capable and supported, their sense of control is high, leading to the usage intention. Thus, we propose the following hypothesis:

H5. Perceived behavioral control positively affects behavioral intention to use chatbot-CRM.

3.9. Resistance to change

Resistance to change (RC) is defined as an individual's tendency to resist or avoid making changes and adopting new approaches of chatbot-CRM (Chatterjee, et al., 2022). This means that employees with a high tendency of RC may prefer human-operated CRM processes or legacy systems and may be unwilling to be involved in the new chatbot-CRM systems. In the early stage of digital transformation in Vietnam, this factor is uniquely important for organizational users as many enterprise technology initiatives fail not due to the technology itself, but due to user resistance. Individuals may fear that the AI will replace or de-skill their jobs, lack trust in the technology's decisions, or just discomfort with new routines. Previous studies indicated that user reluctance and resistance can significantly influence technology adoption in practice (Chatterjee, Chaudhuri, Vrontis, & Jabeen, 2022) (Talwar et al., 2020) (Kwangsawad & Jattamart, 2022). Thus, we propose the following hypothesis:

H6. Resistance to change negatively affects behavioral intention to use chatbot-CRM.

3.10. Behavioral intention to use chatbot-CRM

Behavioral intention (BI) is the dependent variable in our model, representing the tendency of an employee to use the chatbot-CRM in their work. Based on TAM and TPB, prior studies found the positive impact of BI on the actual usage or adoption of AI-integrated CRM systems (Ozay et al., 2024) (Urbani et al., 2024) (Chatterjee, Rana, et al., 2023) (Chatterjee, Chaudhuri, Vrontis, & Jabeen, 2022) (Chatterjee, Chaudhuri, et al., 2021). Thus, this study expects to obtain a reliable indicator of to what extent the determinants encourage actual adoption by examining BI as the outcome, which sets the stage for the successful implementation of chatbot-CRM in Vietnamese organizations. Figure 1 shows our proposed research model.

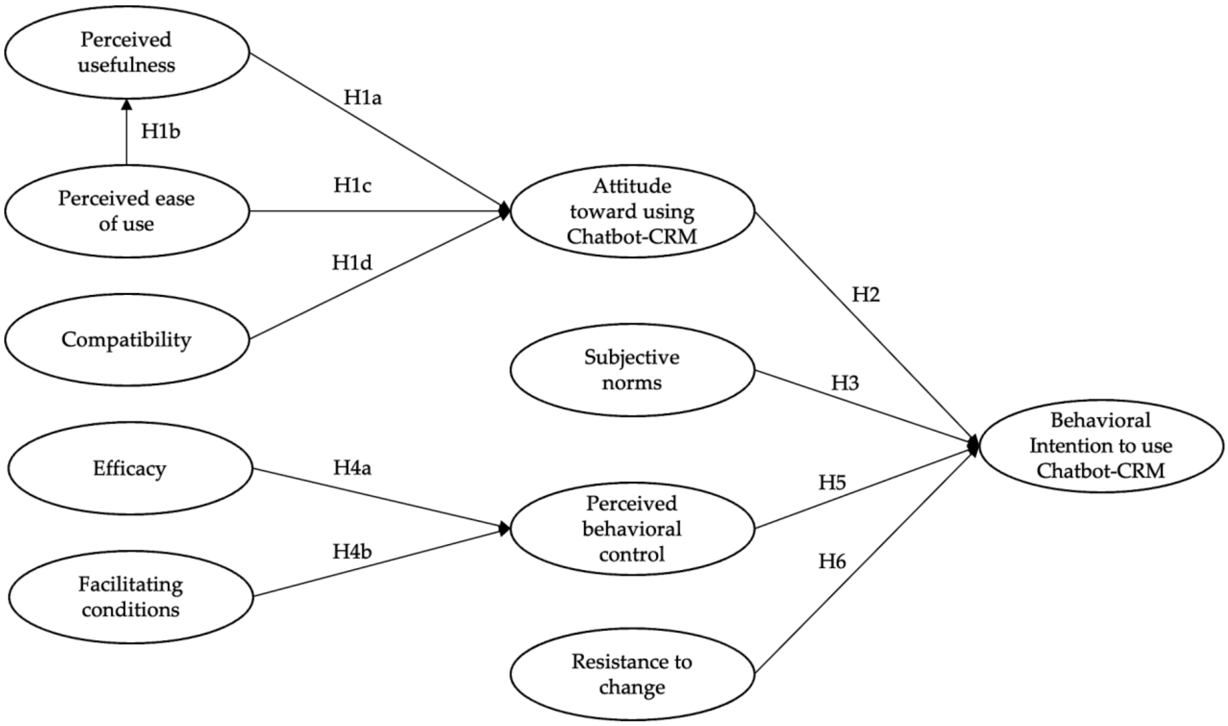

Figure 1. Research model and hypotheses

Source: Authors' model

4. Research methodology

4.1. Measurement development

This study adopts the measures for each construct from the existing literature for validity. The measurements of PU (six items), PEU (six items), COM (three items), AT (four items), SN (three items), E (three items), PBC (four items), and BI (three items) are adopted from Taylor and Todd (1995) and Brachten, et al. (2021). Four items for FC are adopted from Taylor and Todd (1995), Shih and Fang (2004), and Brachten, et al. (2021). Four items for RC are adopted from Chatterjee, et al. (2022). Participants rated each item on a six-point Likert scale, where 1 indicated strong disagreement and 6 indicated strong agreement.

4.2. Data collection

The questionnaire for data collection was designed in Google Forms, a convenient and efficient platform for conducting surveys. The questionnaire was distributed via Gmail, Messenger, and Zalo, to reach a wide range of Vietnamese individuals working in organizations that are deploying CRM systems. Furthermore, the authors used a proactive approach, disseminating the questionnaire offline and leveraging personal relationships and professional networks to increase the response rate. To increase sample size and diversity, the authors asked previous respondents to distribute the questionnaire to their connections. This snowball sampling technique helped to expand the pool of participants and gather views from a wider range of people. This study aimed to collect a more representative sample and improve the generalizability of the findings by leveraging social networks and personal relationships. The survey ran from Jan 14 to Feb 02, 2025, and obtained 193 responses. However, 46 responses were eliminated as the participants' organizations were not using any CRM systems. Thus, a total of 147 responses were valid after data screening. The sample consisted of 60 females (41%), 83 males (56%), and 4 others (3%). The majority of respondents were Staff/ Specialists (46%), indicating a sample largely composed of operational employees. Most respondents were from the IT (29%) and Marketing (23%) departments, followed by Business (17%) and Finance & Accounting (14%). Regarding industry, most participants were from Technology (40%), Retail (25%), and Finance (14%). The most commonly used CRM system among respondents was Pancake (33%), followed by SalesWork (20%), and AntBuddy (20%). Regarding chatbot-CRM experience, most of the participants have less than 3 years of experience (83%), including 20% of participants having no experience in using chatbot-CRM. Table 2 indicates the descriptive statistics of the sample.

5. Data analysis and results

This study used a structural equation model to validate the research model. SmartPLS 4.0 was used to assess the measurement and structural model as the approach is suitable for a sample size was under 500 (Hair et al., 2019). PLS-SEM was chosen over CB-SEM due to its suitability for exploratory models, smaller samples, and its ability to maximize variance explained in key constructs (Hair et al., 2019). We assessed reliability, convergent validity, and discriminant validity for the measurement model using PLS Algorithm calculation. For the structural model, based on the Bootstrap calculation, we evaluated the path coefficients to test the proposed hypotheses.

5.1. Measurement model

Table 3 indicates that the outer loadings of all items are from 0.781 to 0.950, which is above 0.7 (Hair et al., 2019). Cronbach's α and composite reliability of all constructs are greater than the recommended threshold of 0.7. The average variance extracted (AVE) for all constructs is above 0.5 (Fornell & Larcker, 1981). Table 4 demonstrates that the square root of the AVE of each construct is higher than the correlations between the construct and other constructs (Fornell & Larcker, 1981). Table 5 shows that all of the HTMT values are less than 0.9 (Henseler et al., 2016). However, Table 6 shows a VIF value of the item RC2 is above 5, so RC2 was eliminated from the model.

5.2. Structural model

The bootstrap calculation was used to test the proposed hypotheses. Table 1 and Figure 2 show that eight hypotheses, namely H1a, H1b, H1c, H1d, H2, H4a, H4b, and H5, are supported. The original sample indicators show that AT has a stronger impact on BI compared to PBC. Similarly, PU is the key determinant of AT, while E shows a greater influence on PBC than FC. The R-square value for BI is 46.4%.

Table 1. Structural model results

Hypothesis	**Original sample (O)**	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**	**Result**
H1a: PU -> AT	0.367	0.363	0.100	3.652	0.000	Supported
H1b: PEU -> PU	0.786	0.781	0.056	13.912	0.000	Supported
H1c: PEU -> AT	0.360	0.361	0.081	4.434	0.000	Supported
H1d: COM -> AT	0.196	0.194	0.073	2.691	0.007	Supported
H2: AT -> BI	0.526	0.529	0.111	4.734	0.000	Supported
H3: SN -> BI	-0.123	-0.122	0.083	1.485	0.138	Rejected
H4a: E -> PBC	0.450	0.448	0.077	5.881	0.000	Supported
H4b: FC -> PBC	0.389	0.386	0.071	5.455	0.000	Supported
H5: PBC -> BI	0.290	0.279	0.116	2.507	0.012	Supported
H6: RC -> BI	-0.002	-0.010	0.059	0.042	0.967	Rejected

Source: Authors' analysis

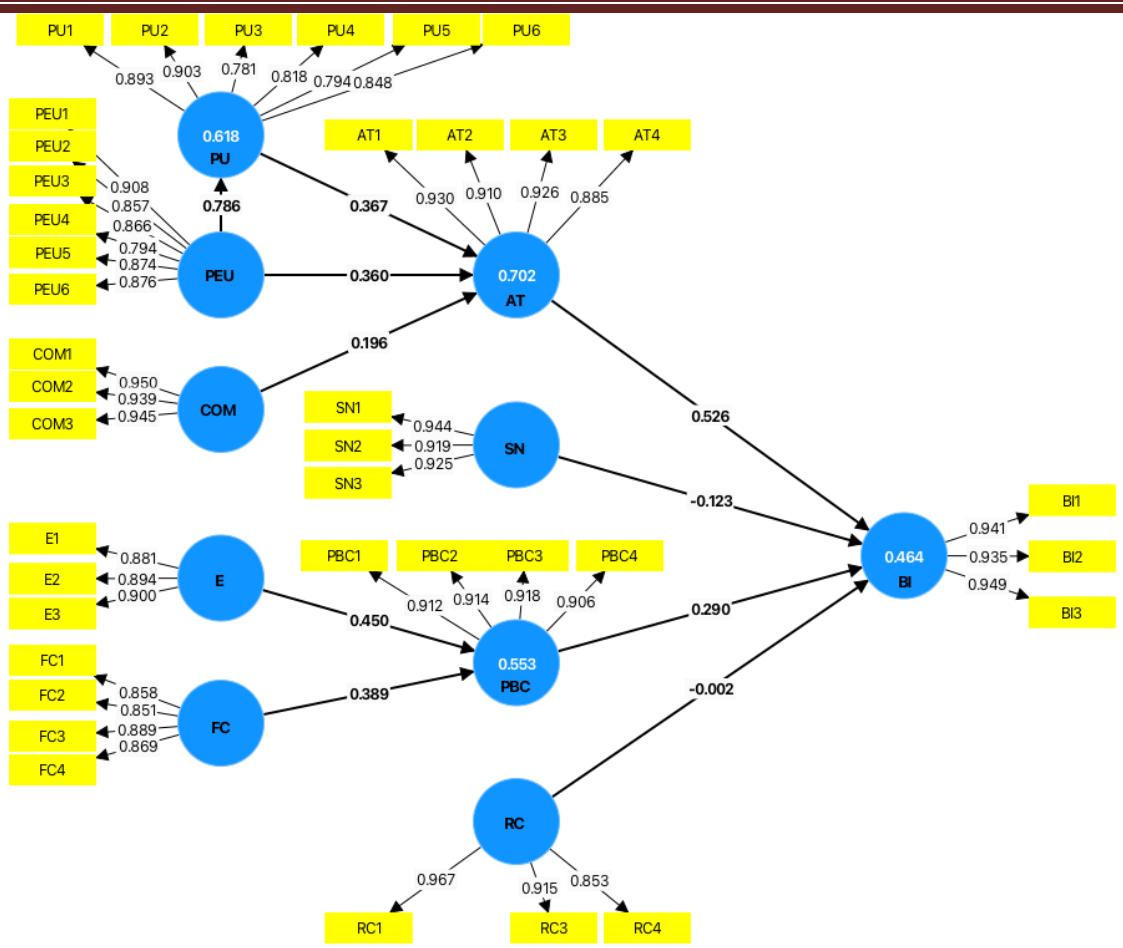

Figure 2. Structural model analysis

Source: Authors' analysis

6. Discussion and implications

6.1. Discussion of findings

The results of this study confirm that both technology-related perceptions and organization readiness factors significantly affect behavioral intention to adopt chatbot-CRM systems among employees in Vietnam. Attitude towards using chatbot-CRM is the most critical factor affecting behavioral intention, which aligns with the foundational TAM and TPB models. This implies that organizational users in Vietnam are more likely to adopt chatbot tools when they develop a positive emotional and cognitive evaluation of the technology, reinforcing the role of attitude found in the prior studies (Chatterjee, Chaudhuri, et al., 2021) (Taylor & Todd, 1995).

The significant impacts of perceived usefulness, perceived ease of use, and compatibility on attitude towards using chatbot-CRM suggests that Vietnamese employees prefer clear, functional benefits and low-complexity interaction when approaching new chatbot-CRM systems with smooth integration into existing workflows. This finding aligns with studies in other emerging markets, such as India and China, while also highlighting context-specific differences. For instance, the studies in India found that the three mentioned factors were significant in Indian enterprises adopting AI-integrated CRM systems, but trust also played an important role (Chatterjee, Rana, et al., 2023) (Chatterjee, Nguyen, et al., 2020) (Chatterjee, Chaudhuri, et al., 2021). However, the research in China indicated that trust significantly mediated the relationships of interactivity and humanness to intention to adopt chatbot for e-commerce (Ding & Najaf, 2024). Our results suggest that in

Vietnam, as many organizations are at varying stages of digital transformation, if a chatbot-CRM system can enhance task efficiency, it is more likely to gain acceptance. Moreover, even a powerful chatbot-CRM may face resistance if it disrupts the daily routines of Vietnamese staff accustomed to manual CRM workflows or informal communication styles.

Perceived behavioral control was found to be a strong predictor of behavioral intention, confirming that confidence and resource availability matter in Vietnamese organizations. Both efficacy and facilitating conditions show significant impacts on perceived behavioral control, which is consistent with the prior studies (Brachten et al., 2021) (Shih & Fang, 2004) (Chaudhuri et al., 2023). This means that employees in Vietnam are more likely to adopt chatbot-CRM when they are confident in using it and know that technical assistance, training, or guidelines are readily accessible.

Interestingly, subjective norms and resistance to change are found not significant determinants of behavioral intention, which is not in line with previous studies (Chatterjee, Chaudhuri, Vrontis, & Jabeen, 2022) (Chatterjee, Nguyen, et al., 2020) (Talwar et al., 2020). In the Vietnamese context, this may reflect an emerging trend of greater individual autonomy among younger employees, especially in industries like IT and marketing, who may evaluate technologies based on personal relevance and utility rather than hierarchical expectations. However, highly resistant employees may have already self-selected out of technology-intensive roles, resulting in a sample with open attitudes.

6.2. Implications

Regarding theoretical implications, this study contributes to the technology adoption literature by examining pre-adoption behavioral intention among internal users across multiple industries with a model tailored to the Vietnamese organizational context. The rejections of subjective norms and resistance to change also challenge commonly accepted assumptions in TPB applications. This theoretical nuance encourages future researchers to account for national culture, organizational readiness, and digital fluency as potential moderators. Furthermore, this study supports the need to reframe technology acceptance not only as a function of personal beliefs but also of organizational system alignment, especially when employees operate in environments that mix traditional and digital workflows.

In terms of practical implications, system designers should focus on streamlining user ễprience by offering chatbot interfaces that are intuitive, easy to navigate, and aligned with existing software ecosystems. Also, Vietnamese companies should consider localized training materials and technical support infrastructure, particularly for those in departments such as finance or sales who may not be digitally native. Next, rather than using top-down mandates or peer influence, leaders should create an environment where employees feel ownership of the tool's implementation, making them understand the tangible benefits of the chatbot-CRM such as reducing repetitive tasks and enhancing service responsiveness. Finally, digital transformation consultants in Vietnam should consider organizational culture and legacy system integration as central to chatbot-CRM success. Customization, interoperability with platforms such as Zalo or Facebook Messenger, and respect for the relational nature of Vietnamese work environments will be critical for effective deployment.

7. Limitations and future research

This study has several limitations. First, the use of snowball sampling and a relatively small sample size limits the generalizability of the findings across industries in Vietnam. Future research should expand the sample to include a broader range of sectors and firm sizes. Second, the cross-sectional approach gathers insights at a single time frame. Future research should utilize longitudinal design for a better assessment of how attitudes and adoption behaviors evolve throughout the deployment process. Third, the model focuses on individual-level factors, while the incorporation of organizational-level factors such as leadership support, digital strategy, or change communication should be examined to provide a more holistic view. Finally, this study examined behavioral intention rather than actual usage. Future studies should include post-adoption behavior and system performance to validate the relationship between intention and behavior.

8. Conclusion

This research explores the determinants of behavioral intention to adopt chatbot-CRM systems among organizational users in Vietnam, based on the application of TAM and TPB models. The integrated model was extended with more factors, namely compatibility, efficacy, facilitating conditions, and resistance to change, to capture both technological perceptions and contextual impacts related to organizational environments in an emerging market such as Vietnam.

The results highlight that attitude towards using chatbot-CRM is the strongest determinant of behavioral intention, affected by perceived usefulness, perceived ease of use, and compatibility. Moreover, perceived behavioral control, shaped by efficacy and facilitating conditions, also significantly contributes to intention. In contrast, subjective norms and resistance to change are found to have no significant influence, suggesting that in the Vietnamese context, adoption decisions are driven more by individual evaluation of utility and support rather than by social pressure or aversion to change. This research contributes to technology adoption in both theoretical and practical aspects.

As Vietnam advances its digital transformation, especially within service-oriented industries, gaining insights into the behavioral factors influencing enterprise technology adoption is becoming increasingly critical. This study offers a timely and context-specific framework to inform future research on technology adoption in Vietnamese organizations.

APPENDIX

Appendix A. Data analysis results

Table 2. Sample characteristics

Characteristic	n	%
Gender		
Male	83	56%
Female	60	41%
Other	4	3%

Job level		
Director/ Deputy Director	6	4%
Head/Deputy Head of Department	19	13%
Team Leader	26	18%
Staff/Specialist	67	46%
Probation	1	1%
Intern	28	19%
Current department		
IT	43	29%
Marketing	34	23%
Business	25	17%
Finance – Accounting	21	14%
Customer Service	20	14%
Others	4	3%
Industry		
Technology	59	40%
Finance	20	14%
Retail	37	25%
Education	12	8%
Others	19	13%
CRM system in the current organization		
Pancake	49	33%
SalesWork	30	20%
AntBuddy	29	20%
StringeeX	19	13%

Fchat	13	9%
Salesforce	3	2%
Zoho	3	2%
Caresoft	1	1%
Chatbot-CRM experience		
No experience	29	20%
Under 1 year	61	41%
1 - < 3 years	32	22%
3 - < 5 years	16	11%
5 years or more	9	6%

Source: Authors' analysis

Table 3. Outer loadings, reliability, and convergent validity

Item	Outer loadings	Cronbach's α	Composite reliability	AVE
AT1	0.930	0.933	0.952	0.833
AT2	0.910			
AT3	0.926			
AT4	0.885			
BI1	0.941	0.936	0.959	0.887
BI2	0.935			
BI3	0.949			
COM1	0.950	0.940	0.961	0.893
COM2	0.939			
COM3	0.945			
E1	0.881	0.871	0.921	0.795
E2	0.894			
E3	0.900			
FC1	0.858	0.890	0.924	0.751

FC2	0.851			
FC3	0.889			
FC4	0.869			
PBC1	0.912	0.933	0.952	0.833
PBC2	0.914			
PBC3	0.918			
PBC4	0.906			
PEU1	0.908	0.931	0.946	0.745
PEU2	0.857			
PEU3	0.866			
PEU4	0.794			
PEU5	0.874			
PEU6	0.876			
PU1	0.893	0.917	0.935	0.707
PU2	0.903			
PU3	0.781			
PU4	0.818			
PU5	0.794			
PU6	0.848			
RC1	0.950	0.941	0.955	0.843
RC2	0.945			
RC3	0.914			
RC4	0.861			
SN1	0.944	0.922	0.950	0.864
SN2	0.919			
SN3	0.925			

Source: Authors' analysis

Table 4. Fornell-Larcker criterion

	AT	**BI**	**COM**	**E**	**FC**	**PBC**	**PEU**	**PU**	**RC**	**SN**
AT	0.913									

BI	0.650	0.942								
COM	0.686	0.566	0.945							
E	0.716	0.618	0.656	0.892						
FC	0.583	0.477	0.613	0.567	0.867					
PBC	0.647	0.558	0.686	0.671	0.645	0.912				
PEU	0.767	0.508	0.605	0.661	0.570	0.534	0.863			
PU	0.795	0.584	0.744	0.732	0.615	0.664	0.786	0.841		
RC	-0.252	-0.160	-0.324	-0.183	-0.110	-0.128	-0.305	-0.305	0.918	
SN	0.521	0.321	0.510	0.467	0.638	0.584	0.474	0.538	-0.089	0.930

Source: Authors' analysis

Table 5. Heterotrait-monotrait ratio (HTMT)

	AT	**BI**	**COM**	**E**	**FC**	**PBC**	**PEU**	**PU**	**RC**	**SN**
AT										
BI	0.693									
COM	0.730	0.602								
E	0.793	0.684	0.722							
FC	0.639	0.521	0.670	0.643						
PBC	0.695	0.596	0.732	0.742	0.706					
PEU	0.816	0.541	0.645	0.730	0.624	0.571				
PU	0.854	0.628	0.801	0.816	0.681	0.717	0.842			
RC	0.256	0.149	0.318	0.168	0.119	0.128	0.304	0.299		
SN	0.556	0.338	0.546	0.516	0.703	0.625	0.508	0.582	0.097	

Source: Authors' analysis

Table 6. Collinearity statistics (VIF)

Items	**VIF**	**Items**	**VIF**	**Items**	**VIF**
BI1	4.233	COM1	4.943	E1	2.132
BI2	3.564	COM2	3.852	E2	2.326
BI3	4.733	COM3	4.340	E3	2.632
SN1	3.598	PEU1	4.100	FC1	2.376
SN2	3.471	PEU2	2.895	FC2	2.344
SN3	3.253	PEU3	2.879	FC3	3.237
AT1	4.230	PEU4	2.267	FC4	3.041

AT2	3.419	PEU5	3.503	RC1	3.924
AT3	4.228	PEU6	2.994	RC2	5.446
AT4	2.780	PU1	3.620	RC3	4.185
PBC1	3.423	PU2	4.033	RC4	3.205
PBC2	3.560	PU3	2.111		
PBC3	3.647	PU4	2.201		
PBC4	3.305	PU5	2.213		
		PU6	2.635		

Source: Authors' analysis

Appendix B. Measurement items

Table 7. Measurement items

Constructs	Code	Items	Sources
Perceived Usefulness (PU)	PU1	I believe that chatbot-CRM systems will bring significant benefits to organizations.	Taylor and Todd (1995); Brachten, et al. (2021)
	PU2	CRM software with integrated chatbots will help organizations develop more effectively.	
	PU3	Chatbot-CRM systems are a key factor for the success of modern business organizations.	
	PU4	Employees will feel comfortable using CRM systems with integrated chatbots.	
	PU5	In developed countries, chatbot-CRM systems have proven to be extremely successful.	
	PU6	Chatbot-CRM systems will be widely accepted if their benefits are clearly recognized.	
Perceived Ease-of-Use (PEU)	PEU1	People will be willing to use chatbot-CRM system if it is user-friendly and easy to use.	Taylor and Todd (1995); Brachten, et al. (2021)
	PEU2	Users will use a chatbot-CRM system if it is user-friendly and easy to use.	
	PEU3	Chatbot-CRM systems are designed to effectively meet the different needs of the organization.	
	PEU4	Operating a chatbot-CRM system is very simple.	
	PEU5	Adequate training will make using a chatbot-CRM system easier.	

	PEU6	Migration from traditional CRM systems to a chatbot-integrated CRM system will be smooth if there is proper support.	
Compatibility (COM)	COM1	Using chatbot-integrated CRM will fit well with the way I work.	Taylor and Todd (1995); Brachten, et al. (2021)
	COM2	Using chatbot-integrated CRM will fit into my work style.	
	COM3	The setup of the chatbot-integrated CRM will be compatible with the way I work.	
Subjective Norms (SN)	SN1	People who influence my behavior would think that I should use chatbot-CRM.	Taylor and Todd (1995); Brachten, et al. (2021)
	SN2	People who are important to me would think that I should use the chatbot-CRM.	
	SN3	People whose opinions I value prefer that I should use chatbot-CRM.	
Facilitating Conditions (FC)	FC1	I have access to the necessary devices to use the chatbot-CRM in my work.	Taylor and Todd (1995); Shih and Fang (2004); Brachten, et al. (2021)
	FC2	I have sufficient time to learn how to use the chatbot-CRM.	
	FC3	Having access to technical support for using the chatbot-CRM is important to me.	
	FC4	Having affordable access to the chatbot-CRM system is important to me.	
Efficacy (E)	E1	Being able to operate the chatbot-CRM on my own is important to me.	Taylor and Todd (1995); Brachten, et al. (2021)
	E2	Knowing enough to operate the chatbot-CRM effectively is important to me.	
	E3	Being comfortable using the chatbot-CRM on my own is important to me.	
Perceived Behavioral Control (PBC)	PBC1	I believe I would be able to operate the chatbot-CRM system if I were to use it.	Taylor and Todd (1995); Brachten, et al. (2021)
	PBC2	Using the chatbot-CRM would be entirely within my control if I were to implement it in my work.	

	PBC3	I believe I have the necessary resources and knowledge to effectively use the chatbot-CRM system if required.	
	PBC4	I am confident that I have the ability to successfully use the chatbot-CRM system if it were introduced in my work.	
Attitude towards Using (A)	A1	Using the chatbot-CRM system is a good idea.	Taylor and Todd (1995); Brachten, et al. (2021)
	A2	Using the chatbot-CRM system is a wise idea.	
	A3	I like the idea of using the chatbot-CRM system.	
	A4	Using the chatbot-CRM system would be pleasant.	
Resistance to Change (RTC)	RTC1	I will not comply with the change to the new way of with chatbot-integrated CRM system.	Chatterjee, et al. (2022)
	RTC2	I will not cooperate with the change to the new way of working with the chatbot-integrated CRM system.	
	RTC3	I oppose the change to the new way of working with chatbot-integrated CRM system.	
	RTC4	I do not agree with the change to the new way of working with chatbot-integrated CRM system.	
Behavioral Intention to Use Chatbot-CRM (BI)	BI1	I intend to use the chatbot-integrated CRM system.	Taylor and Todd (1995); Brachten, et al. (2021)
	BI2	I intend to use the chatbot-CRM to do my future tasks.	
	BI3	I intend to use the chatbot-integrated CRM frequently.	

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